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Supply chain optimization of sugarcane first generation and eucalyptus second generation ethanol production in Brazil

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HIGHLIGHTS

- Optimal location & scale of ethanol plants for expansion in Goiás until 2030.
- Ethanol costs from sugarcane vary between 710 and 752 US$/$m^3$ in 2030.
- For eucalyptus-based ethanol production costs vary between 543 and 560 US$/$m^3$ in 2030.
- System-wide optimization has a marginal impact on overall production costs.
- The overall GHG emission intensity is mainly impacted by former land use.

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ABSTRACT

The expansion of the ethanol industry in Brazil faces two important challenges: to reduce total ethanol production costs and to limit the greenhouse gas (GHG) emission intensity of the ethanol produced. The objective of this study is to economically optimize the scale and location of ethanol production plants given the expected expansion of biomass supply regions. A linear optimization model is utilized to determine the optimal location and scale of sugarcane and eucalyptus industrial processing plants given the projected spatial distribution of the expansion of biomass production in the state of Goiás between 2012 and 2030. Three expansion approaches evaluated the impact on ethanol production costs of expanding an existing industry in one time step (one-step), or multiple time steps (multi-step), or constructing a newly emerging ethanol industry in Goiás (greenfield). In addition, the GHG emission intensity of the optimized ethanol supply chains are calculated. Under the three expansion approaches, the total ethanol production costs of sugarcane ethanol decrease from 894 US$/$m^3$ ethanol in 2015 to 752, 715, and 710 US$/$m^3$ ethanol in 2030 for the multi-step, one step and greenfield expansion respectively. For eucalyptus, ethanol production costs decrease from 635 US$/$m^3$ in 2015 to 560 and 543 US$/$m^3$ in 2030 for the multi-step and one-step approach. A general trend is the use of large scale industrial processing plants, especially towards 2030 due to increased biomass supply. We conclude that a system-wide optimization as a marginal impact on overall production costs. Utilizing all the predefined sugarcane and eucalyptus supply regions up to 2030, the results showed that on average the GHG emission intensity of sugarcane cultivation and processing is −80 kg CO_2/m^3, while eucalyptus GHG emission intensity is 1290 kg CO_2/m^3. This is due to the high proportion of forest land that is expected to be converted to eucalyptus plantations. Future optimization studies may address further economic or GHG emission improvement potential by optimizing the GHG emission intensity or perform a multi-objective optimization procedure.

1. Introduction

The increasing energy demand and the growing awareness of climate change due to fossil fuel related greenhouse gas emissions (GHG) have raised the interest in the use of biomass for energy. As

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Nomenclature

Abbreviations

Bioscope	decision support system using a MILP structure, developed by University Illinois
CPLEX	a GAMS solver designed to solve large, difficult problems with minimal user intervention.
CSP	centralized storage and pre-processing
DSS	decision support system
GAMS	General Algebraic Modelling System
GHG	greenhouse gas
GIS	geographical information system
LP	linear programming
MILP	mixed integer linear programming
SC	supply chain
TC	tonne cane

Indices

i	biomass supply region
k	industrial processing facility location

a result, the global annual biofuel production increased significantly from 153 PJ in 1990 to 1988 PJ in 2012, and is likely to grow even further with increasing biofuel demand [1]. World biofuel production is dominated by ethanol, which originates mainly in the United States of America (USA) and Brazil [2,3]. The large scale production and consumption of bioethanol in Brazil occurred already since the implementation of the Brazilian Alcohol program in 1975 [4]. Due to this experience and know-how, the (mature) industrial processing technology, but also due to the availability of suitable land, Brazil has a large potential to further expand its ethanol production [2,5]. Currently, more than half of the Brazilian sugarcane based first generation ethanol production is located in the Centre South region, especially São Paulo state [6]. However, the sugarcane production in the states of Goiás, Mato Grosso, Mato Grosso do Sul, Minas Gerais and Paraná has expanded rapidly in recent decade [5,6]. Although currently sugarcane is the biomass feedstock for ethanol production in Brazil, the utilization of new industrial processing technologies using ligno-cellulosic feedstock could enable the use of a wider range of biomass feedstock for ethanol production. Eucalyptus cultivation in combination with novel processing technology holds great promise, especially in regions less suitable for sugarcane cultivation [7,8].

The expansion of the ethanol industry in Brazil faces two important challenges. First, the aim to reduce total ethanol production costs in order to compete with fossil fuels and other biofuels. Second, the objective of limit the GHG emission intensity of ethanol production, as biofuels are intended to reduce anthropogenic GHG emissions by fossil fuel replacement. Currently, sugarcane based ethanol from Brazil has low production costs and achieves high GHG emission reduction compared to fossil fuels, but also compared to other biofuels produced worldwide [9]. Total ethanol production costs of different biomass crops in Brazil are mainly determined by land cost, biomass yield, logistics, conversion efficiency and scale of industrial processing [8]. The total GHG emissions intensity of ethanol production is mainly determined by land-use change (LUC) emissions, pre-harvest burning (common for manual sugarcane harvesting), emissions related to fertilizer application [10,11], and emissions related to biomass feedstock transportation. Furthermore, the ethanol conversion efficiency, and the GHG emission credits for the co-production of surplus electricity are important to determine the GHG intensity of ethanol production [10]. In order to assess the costs and GHG performance of the expansion of the ethanol industry in Brazil, these parameters, which are in many cases spatially highly heterogeneous, should be taken into account.

Strategic biofuel supply chain optimization could be applied to optimize the costs and GHG emissions of potential ethanol production chains in Brazil. A strategic supply chain analysis provides insight into the importance of the different variables in the supply chain design and trade-offs between them, such as the trade-off between transport costs and economy of scale of industrial processing. Numerous studies applied strategic biofuel supply chain optimization procedures to select an optimal bioenergy supply chain design, e.g. [12–19]. More detailed, strategic optimization models have been applied to determine the lowest overall biofuel production cost or GHG emissions of the total system design [20–23].

- The optimization study of Mansuy et al. [19] used fire-affected forestry biomass in two forest management units in Eastern Canada. The analysis was performed on a 10 by 10 km grid cell scale and due to the low availability of affected forestry biomass, only a limited amount of pellet plants were required.
- Samsatli et al. [18] used the United Kingdom as case study region for a hypothetical biomass supply chain optimization for both costs and GHG emissions?. The most important drawbacks are; the limited amount of supply regions (160), the coarse resolution of the supply regions and not considering land demand for other purposes.
- In the study of Pettersson et al. [17], the emerging biofuel industry using forestry biomass integrated with existing wood using industry was modelled. Although the biomass availability in this study was based on the detailed assessment of Lundmark et al. [24], which was later aggregated, the study preselected only 51 potential biofuel production sites for whole of Sweden.
- Cobuloglu and Büyüktahtakın [16] used a multi-objective optimization model to maximize profit of a hypothetical biofuel production facility in Kansas, USA using multiple biomass feedstock. The objective function included both costs and the weighted economic value of several environmental impacts. This study included the expansion of biomass cultivation over other land uses in order to supply the biofuel production facility. The square sourcing area is divided into 440 potential biomass supply regions to supply only one biofuel facility; no other biofuel production facilities are considered.
- The study of Liu et al. [15] determined the total profit, fossil energy input, and GHG emissions of biofuel production pathways in China. The results shows the interlinkage of those three elements. However, the study was limited to 25 model supply regions (provinces), of which only 14 were selected as potential locations for biofuel production.

In general, these strategic supply chain analyses are applied for a hypothetical case, for a small amount of biomass supply regions, or present the biomass supply on a very aggregate level. However, the selection of the location, size and type of industrial processing technology of industrial processing plants is determined by the location of biomass supply, transport and type of processing technology to bioenergy [25]. The optimal location of industrial processing plant(s) may differ when optimizing the location of one industrial plant or optimizing a larger region which includes multiple plants. Such system optimization includes the distribution of biomass between the different industrial plants to find the optimal overall solution. The literature reviews of supply chain optimization studies [25,26] concluded that strategic linear programming models for economic optimization (cost reduction or benefit maximization) constitute the majority of supply chain optimization studies, especially the studies focussed on ethanol production. Sharma et al. [26] also highlighted the need to develop large-scale case studies and incorporating other measures than economic objectives, such as environmental measures in biomass supply chain analysis. The review by De Meyer [25] also concluded that in addition to economic objectives also environmental and social objectives, should be included in future work. The reviewed optimization models are usually developed for specific case studies from the producer's point of view. However, the biomass supply chain is strongly determined by the location of biomass cultivation, transport and processing [25].

Given the review above the goal of the present study is threefold;

- First: determine the economically optimal location and scale of all ethanol production plants in Goiás, taken into account the expansion of biomass supply regions between 2012 and 2030. The state of Goiás is selected because it has an existing ethanol industry, but still has a high potential to expand the ethanol production in the future [27]. This expansion not only includes the expansion of cultivation area in great detail, but also the increase of biomass yield and improved conversion efficiency to ethanol up to 2030. This is the first strategic supply chain optimization model that uses the detailed results of a land-use change model, and thereby also considers the land use change dynamics of other land uses in a region. None of the reviewed literature considers a real case study area with large evident expansion in the coming decades. Furthermore, the results of the land use change model provide the spatial distribution of expected expansion of biomass supply regions in great detail. This enables to distinguish the variation in costs of biomass cultivation, land, and transport. This was not found in other supply chain optimization studies. In this study, costs for sugarcane and eucalyptus cultivation, transport and industrial processing are determined, comparing the ethanol production by first generation technology to a second generation technology.
- Second, the strategic supply chain optimization model is applied to three different expansion approaches to gain insight in the impact of expanding an existing industry in one step, or several time steps, or constructing a newly emerging ethanol industry in Goiás. This also provides insight in the difference between the economic optimal location and scale of industrial processing and the current supply chain design.
- Third, the resulting supply chain designs are also used to determine the distribution of available biomass among the industrial plants, the economic cost breakdown of ethanol production up to 2030, and the GHG emission intensity of the ethanol produced. The GHG emission intensity of ethanol production is assessed taking into account both land-use change emissions as well as supply chain GHG emissions. The land-use change emissions are determined for each biomass supply region. Based on the detailed biomass supply assessment, a transport module is developed to determine the distance between the biomass supply regions and potential processing locations, including different road types.

The characteristics of the ethanol expansion region are described in Section 2, followed by a description of the approach, assumptions and equations used in the supply chain optimization in Section 3. Section 4 is an overview of the data used to perform the supply chain optimization. In Section 5, the results of the optimization are presented, followed by the discussion and conclusions in Section 6.

2. Ethanol production in Brazil, sugarcane and eucalyptus cultivation in Goiás

The production of Brazilian ethanol expanded from 0.6 billion litres in 1975/1976 to 24.0 billion litres in 2012/2013 [6]. In 2014 the total area planted with sugarcane was 10.7 Mha [6], approximately 1.2% of the Brazilian land territory [27]. Sugarcane is commonly cultivated in ratoons of 6 years with 5 harvests. Sugarcane cultivation regions can be classified into the traditional region (predominantly Sao Paulo state), North-eastern region (mainly the coastal area in the Northeast of Brazil) and the expansion areas (Goiás, Mato Grosso, Mato Grosso do Sul, Minas Gerais). Availability of land, lower land remuneration, and proper to reasonable conditions for sugarcane cultivation are supporting the expansion of ethanol production in these areas [28]. Next to the expansion of the area also the yield per hectare improved historically [29], and is expected to increase in the future as well [30]. Due to the phase-out of pre-harvest burning, some areas will be excluded for sugarcane cultivation in the future as the topography restricts mechanical harvesting [5].

The sugarcane production in Goiás increased from 13.0 million tonne cane in harvest season 2003–2004 to 62.0 million tonne in season 2013–2014 [6]. In harvest season 2013–2014, the sugarcane has been processed to 1.89 million tonne sugar and 3.88 million cubic metre ethanol [6]. The cultivation in Goiás is mainly in the southern and central municipalities (see SI-1 for a map of current sugarcane cultivation regions and processing locations in Goiás). In the expansion areas, which include Goiás, around 86% of the sugarcane fields are harvested mechanically [28]. In Goiás, 40 sugarcane processing units (both autonomous[1] and annexed[2] plants) are currently installed for sugar and ethanol production. Overall, a wide range of processing capacities is installed in Goiás., Recently build industrial plants follow the general trend that larger units are constructed [31]. An extensive overview of the installed sugarcane processing plants in Goiás is included in the Supplementary information SI.2.

Mello and Rezende [32] estimated the total area of planted eucalyptus in Brazil to be around 6.7 Mha, of which 54.5 kha are located in Goiás in 2012. The cultivation of eucalyptus is mainly concentrated in the north-eastern part of Goiás. Eucalyptus is commonly cultivated in 3 consecutive cycles of 7 years [33]. Between 1970 and today, the average yield of Brazilian eucalyptus increased significantly [34]. Currently, Brazilian eucalyptus is planted for paper and pulp, charcoal, wood products, energy production, oils, tannin extraction, land reclamation, and wind and fire breaks. In Goiás, the eucalyptus production is mainly to supply feedstock for the paper and pulp facilities, sawn wood production and other wood products [35]. Currently, there are no ethanol processing facilities utilizing eucalyptus in Brazil. However, with the increase in eucalyptus yield and development of second generation processing in the future, eucalyptus holds great potential for ethanol production in Brazil [8].

3. Methods

The goal of this study is to optimize the location and size of ethanol production plants for an expanding the biomass supply area, taking into account improvements in biomass yield and conversion efficiency of the two biomass feedstocks up to 2030.

[1] An autonomous industrial processing plant is a facility completely dedicated to ethanol production. However, such plant may use sugarcane or molasses from a sugar production facility as feedstock.

[2] An annexed industrial plant is a facility build next to a sugar production facility. The advantages of this set up are to share infrastructure and systems, but it may also offer flexibility in output product ratio.

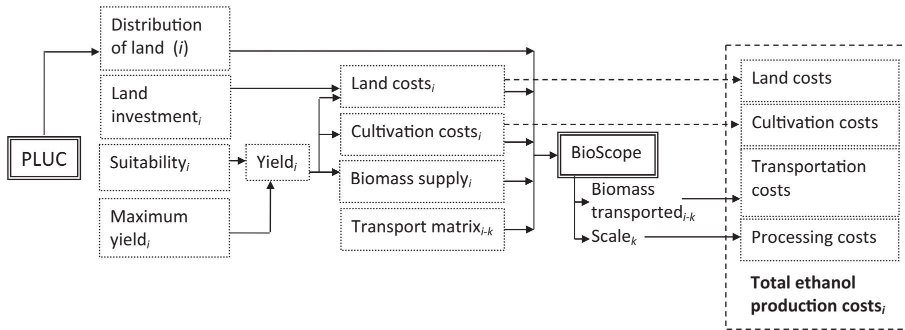

Fig. 1. The main inputs and outputs of the supply chain optimization model used for the Brazilian ethanol supply chain, *i* represent the biomass supply regions and *k* represent the industrial plants.

The optimization problem is to determine the economic optimal supply chain configuration while utilizing the available biomass cultivated in the biomass supply regions. All costs are expressed in US$$_{2014}$. The optimization model objective is to minimize total ethanol production costs while respecting the biomass demand and meet model constraints, e.g.: a supply region can never supply more than it is able to produce, or the total amount of biomass transported to a location may not exceed its processing capacity.

The strategic optimization model considers the ethanol supply chain as a network of biomass supply regions which directly deliver to industrial processing locations. Fig. 1 visualizes the main structure of the supply chain optimization approach, including the data input, intermediate results and final results. The distribution of biomass supply regions (*i*) over the time period 2012–2030 is based on the results of the land use change model PLUC,[3] see [36]. Biomass yield in the supply regions is determined by its suitability for biomass cultivation and the maximum yield in the year of analysis. Biomass yield is also the main variable in land costs, cultivation costs and the total biomass supply in the biomass supply regions considered. By including the transport matrix, the optimization model BioScope[4] is utilized to determine the amount of biomass transported between biomass supply region *i* and the processing plant in location *k*. This amount can be translated into the annual processing capacity or scale of the industrial plant. The total ethanol production costs are the summation of the land costs and cultivation costs of the considered supply regions, transportation costs of the biomass transported between supply regions and the location of industrial processing and the processing costs itself. The key indexes used throughout the model are defined: *i* correspond to the biomass supply regions, and *k* represents the locations of industrial plants. The distribution of biomass supply regions is determined by a land-use change model, as discussed in more detail in Section 3.1. Thereafter, the expansion approach is described (Section 3.2), the BioScope model itself is discussed (Section 3.3), followed by the main elements; biomass cultivation (Section 3.4) biomass transport (Section 3.5) and industrial processing of biomass (Section 3.6).

3.1. Amount and distribution biomass supply regions

The distribution of biomass supply regions (*i*) in Goiás is determined by the PCraster Land Use Change model (PLUC model), a spatially explicit land use change model initially described in [37] and applied for Brazil in [36]. The demand for different land use types between 2012 and 2030 is determined by the global general equilibrium model MAGNET.[5] Based on the development of, among others, population growth, GDP growth, ethanol yield, and biofuel mandates, MAGNET determines the land claim for different land uses for Brazil, which are transferred to PLUC. For Brazil, PLUC determines annual land use maps between 2012 and 2030 and distinguishes 11 different land use types at 5 by 5 km grid cells (supply regions of 2500 ha) [36]. The resulting land use maps of PLUC for the state of Goiás were clipped from the Brazil results, and only the biomass supply regions are considered for this optimization study. In this study the sugarcane supply regions are based on the land category 'sugarcane', while the category 'planted forest' is used as representation of eucalyptus supply regions in Goiás. PLUC uses different suitability factors to allocate the land demand (as determined by MAGNET) over Brazil. For sugarcane allocation the suitability factors are, with their calibrated weight between brackets, existence of sugarcane cultivation in the vicinity (0.29), travel time to existing mills (0.28), potential yield (0.22) and the conversion elasticity from other land uses to sugarcane cultivation (0.21). For eucalyptus, the suitability factors are potential yield (0.37), distance to roads (0.34) and existence of planted forest in the vicinity (0.29). These suitability factors are used as fixed, although each factor has a probability distribution; this distribution and the average may change in the future, as discussed in [38].

3.2. Expansion approach

Most studies optimize the bioenergy supply chain as a newly emerging industry in an area. However, in Goiás, an existing industry is in place, which influences the optimal location of new industrial plants in that region. A detailed overview of existing sugarcane processing plants is shown in SI-2. To show potential differences, the optimization model procedure is applied for three different expansion approaches: multi-step, one-step and greenfield expansion. The multi-step expansion takes into account existing sugarcane fields and processing plants, and assumes additions of new supply regions and processing plants between 2012 and 2030 in 4 time steps (2015, 2020, 2025 and 2030). Each time step considers the location and scale of industrial processing plants from the previous time step, including the existing industrial plants in 2012 and determines the optimal supply chain design for the newly added plants. The one-step optimization uses the total amount of biomass supply regions available in 2030, and carries out the optimization in a single step, representing perfect foresight of the location of biomass supply regions. Finally, the

[3] PLUC is developed by the University Utrecht as a land use change model. See [37] for more information on the model development and the utilization of this model for bioenergy crops in Mozambique.

[4] BioScope is developed by the University of Illinois as strategic economic supply chain optimisation model. The optimization procedure of BioScope is a Mixed Integer Linear Programming (MILP) model, using a CPLEX solver in [21].

[5] The Modular Applied GeNeral Equilibrium Tool (MAGNET) is developed by the LEI (Landbouw Economisch Instituut) and is based on the LEITAP model [55].

greenfield approach considers the same biomass supply regions in 2030, but will not take into account the currently installed industrial processing locations. All approaches consider exogenous improvements of biomass yield, scale of industrial processing and industrial processing conversion efficiency up to 2030, based on data from [8]. After the economic optimization, the GHG emission intensity of ethanol is determined, including direct land-use change emissions.

3.3. Bioscope model

The expected expansion of the ethanol processing facilities in Goiás is optimized through the use of the BioScope model. See [21] for more information on the model structure. The overall modelling objective function for the model is given by Eq. (1); minimization of the overall ethanol production costs for all biomass supply regions in Goiás.[6] The equation represents the total cost of ethanol production and includes the land costs (LC_{iy}) biomass cultivation costs (BCC_{iy}), the biomass transport costs (BTC_{i-ky}), and the industrial processing costs (IPC_{ky}). The industrial processing costs include potential revenues of electricity surplus.

$$EPC_{iy} = \frac{LC_{iy} + BCC_{iy} + BTC_{i-ky}}{EtOH_y} + IPC_{ky} \quad (1)$$

EPC_{iy}	Ethanol production cost for supply region i in year y	US$/m^3 ethanol
LC	Land cost in supply region i in year y	US$/tonne biomass
BCC_{iy}	Biomass cultivation cost in supply region i in year y	US$/tonne biomass
BTC_{i-ky}	Biomass transport cost between biomass supply region i and industrial plant location k in year y	US$/tonne biomass
$EtOH_y$	Biomass conversion efficiency in year y	m^3 ethanol/tonne biomass
IPC_{ky}	Industrial processing cost of plant k in year y	US$/m^3 ethanol

The data regarding biomass availability in the biomass supply regions (i), the costs data regarding cultivation, transport and the capital and operational costs of biomass processing are exogenously determined and supplied to the BioScope optimization model. The key output of the model is a list of the locations and scales of the industrial processing facilities and a list of the amount of biomass transported from each biomass region(s) to the existing and selected new industrial processing location(s). These results are later used to determine the total ethanol production costs per biomass supply region, as depicted in Fig. 1.

3.4. Biomass supply

The total potential biomass availability of sugarcane or eucalyptus in each supply region (i) is a function of suitability and potential maximum yield, as described in Eq. (2). The agro-ecological suitability is based on the suitability data of GAEZ, see [39,40].

$$Sup_{iy} = S_i \times M_Y \times A \quad (2)$$

Sup_{iy}	Biomass supply potential in region i in year y	tonne/year in biomass supply region i
S_i	Suitability of land at location i	% of maximum biomass yield
M_Y	Maximum attainable yield in year y	tonne/ha-year
A	Area per biomass supply region	2500 ha/biomass supply region

3.5. Biomass cultivation

The biomass cultivation costs of sugarcane and eucalyptus are determined using Eq. (3) and supplied as input for the BioScope model. Based on the detailed cost assessment of [8], a non-linear relationship between biomass cultivation costs and biomass yield was established. For the current study, the biomass cultivation costs are simplified to Eq. (3), in which biomass yield is the important (spatial) variable. Cost factor a includes the costs for plantation management per hectare, e.g. soil preparation, planting, application of herbicides. Cost factor b includes the use of fertilizers and harvesting, expressed in US$/tonne. Land costs consider the land remuneration (spatially heterogeneous) and the land conversion costs, and are separately determined, see SI-4 for the calculation on land value. For both factor a and b, all costs are already discounted with an discount rate of 12%, similar to [8]. Cost component c includes all additional costs, expressed as a percentage of the total biomass cultivation costs.

$$BCC_{iy} = \frac{\left(\frac{a}{Y_{iy}}\right) + b}{(1 - c)} \quad (3)$$

BCC_{iy}	Biomass cultivation cost in biomass supply region i in year y	US$/tonne
a	Cost for areal management practices and inputs	US$/ha-year
b	Cost per tonne biomass	US$/tonne
c	Administrative/other cost	% of total cultivation costs
Y_{iy}	Biomass yield in biomass supply region i in year y	tonne/ha-year

The expansion of the biomass supply regions results in land use change from cropland, pasture or forested land to biomass cultivation areas. This could result in land use change emissions due to a change in carbon stock. In this study, the IPCC approach is applied to determine carbon accumulation or carbon emissions due to land use change [41]. This approach includes the carbon stock change in above ground biomass, below ground biomass, and soil organic carbon. For each potential biomass supply region the carbon stock change is the difference between the new carbon stock and the carbon stock of the biomass supply region in 2006, which is considered the former carbon stock. The year 2006 is the most recent year for which the land use map and agricultural databases were available to create a detailed initial land use map [36]. As specified by Eq. (4), the carbon stock change is annualized by 20 years, similar to the IPCC and the RED policy for liquid biofuels [41,42] and thereafter converted to CO_2 emissions by the factor (44/12).

$$C_i = \frac{C_{former i} - C_{new i}}{A_{period}} \times (C_{conversion}) \quad (4)$$

[6] Although the original model formulation of BioScope entailed the use of preprocessing and storage facilities, this is disabled for the application of this model on the Brazilian ethanol industry as sugarcane storage is uncommon in Brazil.

C_i	Carbon dioxide emissions due to land conversion in region i	tonne CO_{2eq}/year
C_{former}	Carbon stock former land use in region i	tonne carbon/ha
C_{new}	Average carbon stock of new biomass plantation in region i	tonne carbon/ha
A_{period}	Annualizing period; to annualize the land use change emissions	20 years
$C_{conversion}$	Carbon dioxide to carbon conversion ratio	44/12

The GHG emissions of biomass cultivation include the consumption of diesel, fertilizers and agrochemicals and are shown in Eq. (5). A detailed overview of cultivation inputs over the lifetime of a sugarcane or eucalyptus plantation and the GHG emission intensities is provided in SI-3. The emission intensities of the fuels, fertilizers and chemicals are based on emission databases, and other scientific literature, see SI-3 for a detailed overview. The GHG emissions related to fertilizer consumption, the use of agro-chemicals and the application of vinasse, filtercake and forestry residues are considered and expressed in an emission factor a or b. GHG emission factor a includes the annualised GHG emissions per hectare, while factor b includes all GHG emissions per tonne biomass.

$$\mathrm{BCE}_{iy} = \left(\frac{a}{Y_{iy}}\right) + b + \left(\frac{C_i}{Y_{iy}}\right) \tag{5}$$

BCE_i	Biomass cultivation GHG emissions in biomass supply region i in year y	g CO_{2eq}/tonne
a	Annualised GHG emissions per hectare	g CO_{2eq}/ha-year
b	GHG Emissions per tonne biomass	g CO_{2eq}/tonne
C_i	Carbon stock change due to land conversion in region i	g CO_{2eq}/ha-year
Y_{iy}	Biomass annual yield in supply region i in year y	tonne/ha-year

3.6. Biomass transport

Biomass transport between biomass supply regions and industrial processing locations is performed by truck. Transportation cost and transport emissions are the sum of costs or emissions for transporting biomass from the field to the industrial processing plants over the road network in Goiás. In this study, three different road types are distinguished: primary asphalt roads (1), secondary roads (2) and dirt roads (3), each with a specific average speed and fuel consumption. For each potential location of an industrial processing facility, a map is computed that indicates for each field the accumulated costs (or emissions) of transporting the feedstock to this industrial plant location. Herein, it is assumed that the truck will take the fastest route. The calculation of this stack of maps is automated using the PCRaster Python framework [43]. Next, the stack of maps is converted to a single matrix, indicating the total transport costs (BTC_{ik}) or biomass transport emission (BTE_{ik}) from each biomass supply region to each potential location of industrial plant. The used data is derived from [8], and considers a relationship between truck velocity, distance, and biomass transport costs by truck. The total biomass transport cost consider the transport costs of the three different road types (road type 1, 2 and 3), as shown in Eq. (6). Cost factor a represent the transportation costs which are time depended, cost factor b represents the costs per km transhipment, both already account for the empty return trip. Cost item c present the fixed transportation costs, for example associated with loading and unloading.

$$\mathrm{BTC}_{ik} = \sum_R \left(\left(\left(\frac{a}{V_R} \right) + b \right) \times D_{i-k} \right) + c \tag{6}$$

BTC_{ik}	Biomass transportation cost between biomass supply region i and industrial processing plant location k	US\$/tonne
a	Cost factor a	US\$/(tonne/h)
b	Variable biomass transport cost per tonne-km biomass transported	US\$/tonne-km
c	Fixed transportation cost per tonne biomass	US\$/tonne
D_{i-k}	Distance between biomass cultivation region in i and industrial plant in location k	km
V_R	Truck speed on specific road type (R: 1, 2 and 3)	km/h

3.6.1. Greenhouse gas emissions biomass transport

Total GHG emissions of biomass transport include the GHG emissions of the specific diesel consumption, related to truck speed on the distinguished road types for the transport trajectory between supply region and industrial location. Eq. (7) describes the total GHG emission of biomass transport between the biomass supply region and an industrial processing location. As the distance (D_{i-k}) is for a single trip, the empty return is taken into account by an empty return factor.

$$\mathrm{BTE}_{ik} = \sum_R \left(\left(\frac{D_{use-R} \times D_{emissions} \times F_{return}}{\mathrm{Load}} \right) \times D_{i-k} \right) \tag{7}$$

BTE	Biomass transportation emissions	g CO_{2eq}/tonne
D_{use-R}	Diesel use of the truck on selected road type (R: 1, 2 and 3)	l/km truck
$D_{emissions}$	GHG emission intensity of diesel	CO_{2eq}/l
F_{return}	Factor empty return trip	[–]
Load	Truck biomass load	tonne/truck
D_{i-k}	Total distance of a single trip between biomass supply region (i) and industrial plant (k)	km

3.7. Industrial processing of biomass to ethanol and electricity

The industrial processing costs of biomass to ethanol are a combination of capital depreciation, operational costs and electricity revenues. The capital costs of an industrial processing facility is assumed to be heavily dependent upon the scale of the facility. Industrial processing scale is an important variable within the BioScope model. To enable the embedding of this variable into the linear optimization model, a linear relationship between the total capital investment and industrial scale is assumed, similar to [21]. See Eq. (8) for this linear relationship, where capital cost factors a and b depend upon the type of industrial processing plant, and also the operational costs and revenues for electricity surplus are taken into account in the total processing cost. The scale of industrial processing plants are restricted by a maximum scale: when the biomass supply to a processing plant reaches this maximum capacity, the biomass is redirected to another industrial processing facility. The operational costs of industrial processing include variable costs of operations related to labour, utilities and maintenance. As an approximation, it is assumed that the operational expenses are linearly dependent upon the processing capacity of the industrial plants. Both the capital investment and operational costs are based on the detailed economic analysis, performed by [8]. The map of the current situation (year 2012) of the ethanol industry in Goiás shows that industrial processing facilities are in, or in close proximity of biomass supply regions. Therefore, all biomass supply regions in Goiás are considered as candidate locations of industrial processing. Considering all regions in Goiás as candidate locations of industrial processing would prolong the computing time considerably.

$$\mathrm{IPC}_k = \frac{\alpha((a \times S_k) + b)}{\mathrm{output}} + \mathrm{opex} - \mathrm{elec} \tag{8}$$

IPC_K	Scale dependent industrial processing cost of industrial facility k	US\$/m^3 ethanol
α	Annuity factor	1/year
a	Capital investment cost factor a of industrial scale k	US\$/(tonne/h)
b	Capital investment cost factor b of industrial scale k	US\$
S_k	Scale of industrial processing plant k	tonne/h
opex	Operational expenses of industrial processing	US\$/m^3 ethanol
Elec	Electricity revenues	US\$/m^3 ethanol
Output	Annual ethanol output of the plant in location k	m^3 ethanol/year

3.7.1. GHG emission of industrial processing

To determine the GHG emissions of industrial processing, the GHG emissions related to the chemical and the energy inputs are taken into account (see Eq. (9)). The GHG emissions related to the construction of the industrial plant are neglected as these are difficult to estimate and play a minor role [44]. The GHG emissions of industrial processing are based on other scientific publications and expressed per tonne of biomass input or per m^3 ethanol output. When considering the GHG emissions per tonne biomass input, the ethanol production efficiency is accounted for. Avoided emissions related to electricity surplus are included in the operational GHG emissions, I_{GHG-t} or I_{GHG-v}.

$$\mathrm{IPE}_k = \frac{I_{\mathrm{GHG}-t}}{\eta} \quad \text{or} \quad I_{\mathrm{GHG}-v} \tag{9}$$

IPE_k	Greenhouse gas emissions of industrial processing of biomass to ethanol	g CO_{2eq}/m^3 ethanol
$I_{\mathrm{GHG}-t}$	GHG emission of industrial processing per tonne input	g CO_{2eq}/tonne biomass
η	Ethanol conversion efficiency	m^3 ethanol/tonne biomass
$I_{\mathrm{GHG}-v}$	GHG emission of industrial processing per cubic metre ethanol	g CO_{2eq}/m^3 ethanol

3.7.2. Ethanol yield

Although industrial processing plants all utilizes the same industrial technology, the ethanol yield per tonne of biomass changes over time for both sugarcane as well as eucalyptus, as sugar content increases and industrial efficiencies of new plants are assumed to be higher compared to older facilities. The ethanol yield is defined by Eq. (10) and include the increase in sugar content, conversion efficiency, and maximum ethanol yield per tonne of biomass. For eucalyptus, the sugar content in Eq. (10) is not used, but the industrial processing efficiency does improve, and the maximum ethanol yield is expressed as ethanol yield per tonne biomass.

$$\mathrm{EtOH}_y = \mathrm{sc}_y \times \eta_c \times \max \tag{10}$$

EtOH_y	Ethanol yield on biomass in year y of industrial processing	m^3/tonne biomass
Sc_y	Sugar content of sugarcane in year y	kg sugar/tonne sugarcane
η_c	Conversion efficiency of industrial processing of industrial plant k in year of construction.	%
max	Maximal ethanol yield on sugar/biomass for sugarcane or eucalyptus	m^3 ethanol/kg sugar or tonne biomass

4. Data input

4.1. Biomass supply regions

As indicated in Fig. 1 the prime data input is the list (location and biomass production of the supply regions) of biomass supply regions (i), which expand between 2012 and 2030 as defined by the land use model PLUC. The amount of biomass supply regions (i) taken into account per year, and the parameters to determine the potential biomass supply of sugarcane or eucalyptus per supply region (Sup_i) using Eq. (2), are shown in Table 1.

4.2. Biomass cultivation costs and GHG emissions

Table 2 summarizes the parameters used to determine the cultivation costs and GHG emissions of sugarcane and eucalyptus cultivation, using Eqs. (3) and (5). The values summarize the detailed cultivation cost breakdown of sugarcane and eucalyptus, shown in [8]. See Appendix SI-3 and SI-4 for a more detailed overview of land costs and overview of the cultivation costs and GHG emissions respectively. The economic parameters in Table 2 include components expressed per ha (subtotal a) and parameters expressed per tonne of harvested biomass (subtotal b). Table 2 also includes the GHG emissions of machinery utilization and agricultural or silvicultural inputs of sugarcane and eucalyptus cultivation are presented.

4.3. Biomass transport

The total transport distance, between biomass supply regions and potential locations of industrial processing plants, is the sum of the distances of different road types. BioScope input is the transport matrix which describes the total transport costs per tonne biomass between supply regions and potential locations of industrial processing plants. Potential locations for industrial processing include all biomass supply regions. Truck velocity is

Table 1
Biomass supply parameters.

		Sugarcane	Eucalyptus	Reference
Total biomass supply regions (kha)	2012	339 (848)	–	[37]
	2015	404 (1010)	141 (353)	
	2020	658 (1645)	347 (868)	
	2025	719 (1798)	537 (1343)	
	2030	780 (1950)	751 (1878)	
Agro-ecological suitability factor range (all years)[A]		0.118–0.521	0.284–0.740	[39]
Maximum potential biomass yield for 2012		180 TC/ha-year[B]	24 dry tonne/ha-year[C]	
Annual biomass yield increase[D]		0.9% per year	2% per year	[8]

[A] Agro-ecological suitability entails the suitability of this supply regions for the cultivation of sugarcane or eucalyptus, expressed as yield factor, e.g. percentage of maximum attainable yield.
[B] The maximum biomass yield of sugarcane is chosen as such that the total sugarcane supply in 2012 matches the total annual production of 2012 [6].
[C] Maximum biomass yield of eucalyptus is selected to yield an average eucalyptus yield in line with the expected average yield of eucalyptus as presented by [45].
[D] The increase of sugarcane and eucalyptus yield is based on yield trends in [8].

Table 2
Economic and GHG emission data parameters for the cultivation of sugarcane and eucalyptus.

Biomass type	Parameter (a, b or c corresponds to parameter in Eqs. (3) or (5))	Economic value	Unit	GHG value	Unit
	Subtotal (*a*) land	3015–6200[A]	US$/ha	–	
Sugarcane	Subtotal (*a*)	1432[B]	US$/ha	366[E]	kg CO_2/ha
	Subtotal (*b*)	17.93[C]	US$/tonne	15.22[F]	kg CO_2/TC
	Administrative cost (*c*)	6%[D]	%	–	
Eucalyptus	Subtotal (*a*)	450.47[B]	US$/ha	111[G]	kg CO_2/ha
	Subtotal (*b*)	6.593[C]	US$/tonne	15.05[H]	kg CO_2/tonne dry
	Administrative cost (c)	6%[D]	%		

[A] Land costs in Goiás vary according to current land use and vary per region in Goiás [46], see SI-4 for a detailed overview of the considered land costs.
[B] Subtotal of cultivation costs which are related to the application of limestone, herbicides and insecticides.
[C] Subtotal of cultivation costs expressed in US$/tonne.
[D] An additional 6% is included in the cultivation costs to account for administrative expenses, similar to [8].
[E] Include the GHG emissions of diesel consumption (excluding harvesting) and the GHG emissions related to the applications of limestone, herbicides and insecticides.
[F] Include the GHG emissions for diesel consumption related to harvesting, fertilizer application (including production), filtercake and vinasse application and trash left in the field.
[G] Include the GHG emissions of diesel consumption (excluding harvesting) and the GHG emissions related to the applications of limestone and herbicides.
[H] Include the GHG emissions of diesel consumption related to tree harvesting, fertilizer application (including production) and forestry residues left onsite.

Table 3
Economic and greenhouse gas emission data for biomass transport.

			Road type		
			Dirt roads	Secondary road	Highway
Speed[A]			15 km/h	55 km/h	80 km/h
Diesel consumption[B]		l/km	0.83	0.37	0.90
Truck loading[C]		tonne/truck	30		
Transport cost parameters[D]	Subtotal (*a*)	US$/tonne-km	2.68		
	Subtotal (*b*)	$US\$_{cent}$/tonne-km	6.35	4.07	3.56
	Subtotal (*c*)	US$/tonne	2.0		
GHG emissions[E]		gram CO_{2eq}/tonne-km	145	65	70

[A] Different truck speeds have been selected to account for the main road types for biomass transport.
[B] Diesel use is based on [47] in which the diesel consumption as function of truck velocity is plotted. The diesel use is adjusted to a larger truck size.
[C] Truck loading of a sugarcane truck is approximately 30 tonne wet cane/truck [48].
[D] More detailed information about the build-up of different costs parameters, see Supplementary information SI-5.
[E] Truck transport emissions are determined with Eq. (7), using a factor for empty return of 1.4 meaning the fuel consumption for an empty trip is only 40% of a full loaded trip', similar to [49]. Emissions factor of diesel in Brazilian transport is based on the GHG intensity of diesel production and consumption 24.1 g C/MJ diesel [50] and Higher Heating Value of diesel of 44 MJ/l, as specified by [49].

considered as the main determinant for difference in transportation costs, see Table 3.

4.4. Industrial processing of biomass to ethanol

The capital and operational cost parameters of first generation sugarcane processing and second generation eucalyptus processing are presented in Table 4. The capital expenses of industrial processing are scale dependent but non-linear due to the scale factors of the different components [8]. To consider the economy of scale in the linear optimization model, two scale ranges are considered in this analysis to fit the non-linear relationship, similar to [21]. Operational costs include chemicals, labour, and operating & maintenance, and are expressed in US$/tonne biomass input. Electricity is produced with a residue-fed steam boiler (86% thermal efficiency [51]), followed by a condensing extracting steam turbine. The residual sugarcane bagasse (for first generation) and unreacted solids (for second generation technology) are utilized in the cogeneration unit. A part of the generated steam is extracted for the distillation process. For first generation industrial processing, the cogeneration unit generates an electricity surplus of 81.6 kW h/tonne cane. In second generation

Table 4
Economic and greenhouse gas emissions data of industrial processing of first and second generation processing.

			Scale range	
First generation			100–999 TC/h[A]	1000–2000 TC/h
		Days of operation	170 days/year[B]	
	Capex cost parameter a	US$	75.57[C]	59.09[C]
	Capex cost parameter b	US$	40×10^6[C]	100×10^6[C]
	Operational costs	US$/tonne cane	8.88[D]	
	GHG emissions	kg CO_2/tonne cane	4.45[E]	
	Electricity surplus	kW h electricity/tonne input	81.6[F]	
	Ethanol yield	l/tonne cane	83–92[G]	
	Maximum capacity	Mtonne cane/year (year)	4.0 (2012)/5.0 (2020)/5.5 (2030)[H]	
Second generation		scale range	25–74 dry tonne/h[I]	75–500 dry tonne/h[I]
		days of operation	300 days/year[J]	
	Capex cost parameter a	US$	469.01[C]	394.40[C]
	Capex cost parameter b	US$	40×10^6[C]	80×10^6[C]
	Operational costs	US$/$m^3$ ethanol	153[K]	
	GHG emissions	g CO_2/l	44.52[L]	
	Electricity surplus	kW h electricity/tonne input	428–220[M]	
	Ethanol yield	l/tonne biomass	293–377[N]	
	Maximum capacity	Mtonne dry biomass/year (year)	0.72 (2015)/1.46 (2020)/3.06 (2030)[O]	

[A] Low range and high range of sugarcane processing capacity of first generation industrial processing.
[B] Operational window is related to the sugarcane harvesting window, similar to [8].
[C] Capital expenses parameters a and b, see Eq. (10), are derived from [8], in which the capital costs of first and second generation industrial processing is discussed, including scaling factors for the major components of the industrial processing plant.
[D] Total operational expenses of first generation processing is 8.88 US$/tonne cane [8].
[E] GHG emissions of ethanol production is 2.6 g CO_2/MJ and an ethanol yield of 81.1 l/TC [52].
[F] For first generation industrial processing, surplus electricity is produced using sugarcane bagasse as feedstock for a high pressure boiler (86% thermal efficiency [51]), followed by steam turbine. Based on the data provided by Dias et al [51], this setup results in an electricity surplus of 81.6 kW h/tonne cane.
[G] Ethanol yield increasing from 83 l/TC in 2015 to 92 l/TC in 2030, due to increasing sugar content 14.9–16.0 and increasing industrial efficiencies [8].
[H] Maximum industrial processing capacity increases over time; 4 million tonne cane/year in 2012, 5.0 M tc/year in 2020 to 5.5 Mtonne cane/year in 2030 [53].
[I] Low range and high range of eucalyptus processing capacity of second generation industrial processing.
[J] Operational window similar to [8].
[K] Total operational expenses of second generation processing is 153 US$/tonne biomass input [8].
[L] GHG emissions of second generation ethanol processing of eucalyptus is expressed by [54] as 2.1 g CO_2/MJ ethanol.
[M] For second generation processing, surplus electricity is produced by using the lignin fraction and unfermented sugars as fuel for the boiler (thermal efficiency 86%). Steam is used in a steam turbine to produce electricity, although part of the steam is extracted for distillation [8].
[N] The ethanol yield of eucalyptus processing increases from 293 l ethanol/dry tonne eucalyptus to 377 l/dry tonne [8].
[O] Maximum industrial processing capacity of second generation increases over time by following the trend of HHV biomass input as specified by [49].

industrial processing, the ethanol conversion efficiency is assumed to increase over time resulting in less unreacted solids available for steam production in the future, Therefore, the surplus electricity reduces from 428 kW h/tonne in 2015 to 220 kW h/tonne in 2030. Electricity revenues expressed in US$/tonne biomass input, are based on the electricity surplus and electricity prices.

5. Results

5.1. Maps of the expansion of ethanol processing plants

In Figs. 2–6, maps show the biomass supply regions and the industrial processing facilities in 2030. The current and expanded biomass supply regions are highlighted with shades of green. As the biomass supply regions are pre-determined, the three different expansion approaches are based on the same distribution of supply regions in 2030. The total biomass supply in 2030 is higher compared to 2012 due to improved biomass yield as well as the expansion of biomass supply regions. The optimization model locates industrial plants according to available biomass supply. Industrial plants are depicted with a red dot (existing industrial plants for sugar or ethanol production) or black dot (new industrial plants for ethanol production). The capacity of industrial processing plants is depicted by the size of the dot. 5 different size ranges are distinguished. Biomass supply regions with identical colour deliver to the same industrial plant, supply regions with a hatched pattern deliver biomass to more than one industrial plant. As the optimization is applied for different time steps until 2030, in each time step the industrial processing capacity matches the total biomass supply.

For the maps of sugarcane cultivation in Figs. 2, 3 and 5, the expansion of the sugarcane supply regions is mainly northwest of the existing sugarcane fields in the South of Goiás, depicted by the zoom area in Figs. 2–4. Especially in the new biomass supply regions (highlighted in the zoom area), large scale industrial processing plants are proposed by the optimization model. In general, the optimization model selects large industrial processing plants due to the economies of scale; only in regions which are not able to supply large industrial plants with enough sugarcane, the industrial scale is smaller. For the multi-step (Fig. 2) and one-step approach (Fig. 3), the already existing industrial plants are complemented with new industrial plants to process the total biomass supply in 2030. The multi-step optimization approach (Fig. 2) results in a total of 59 plants compared to 56 industrial processing plants for the one-step optimization approach (Fig. 3). The multi-step approach results in more industrial plants, as yield increases between each time step but the capacity of industrial plants is fixed once constructed. To utilize the additional biomass supply in each time step, new industrial plants with relatively small processing capacity are needed. The greenfield optimization approach (Fig. 4), yields 29 industrial processing plants, slightly less compared to the current situation (depicted in SI-1). The greenfield approach (Fig. 4) results in the lowest number of industrial plants due to the preference of large scale plants: around half of the total industrial plants have the maximum allowable industrial capacity in 2030. Although there are small differences among the expansion approaches in the location and scale of

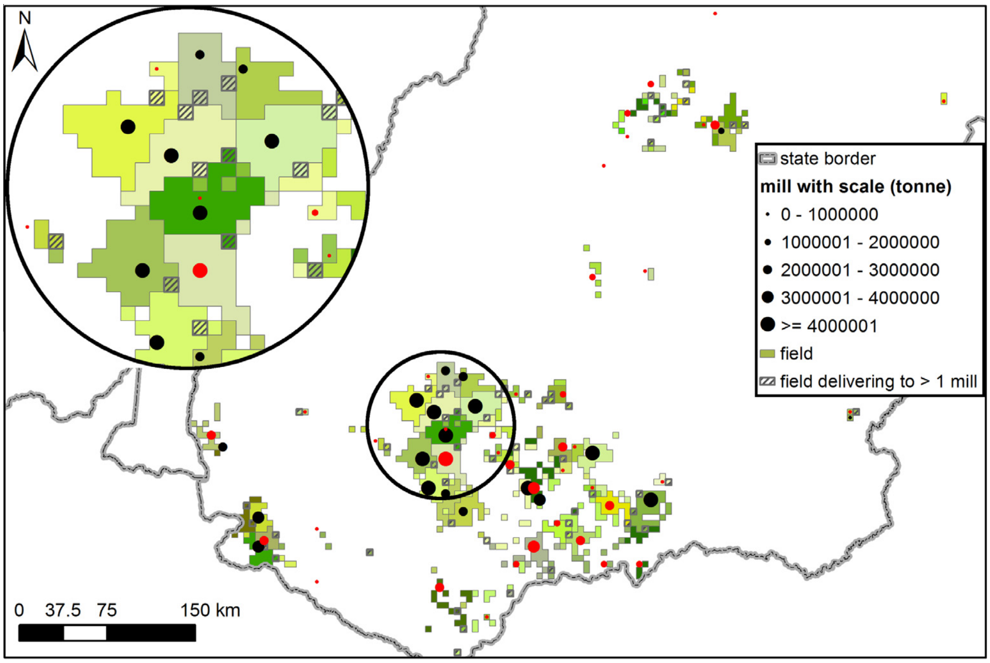

Fig. 2. Map of the multi-step optimization approach (2012, 2015, 2020, 2025 and 2030) of the sugarcane supply regions in green and industrial plants (red circles represent existing industrial plants for sugar or ethanol production, black circles represent new industrial plants for ethanol production) in 2030. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

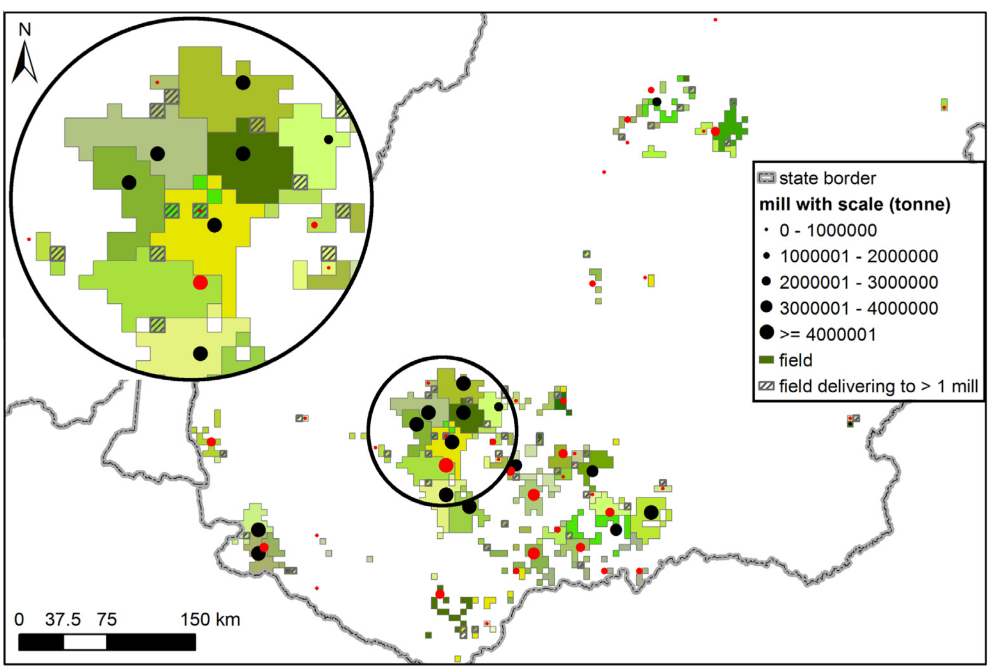

Fig. 3. Map of the one-step optimization approach (2012–2030) of the sugarcane supply regions in green and industrial plants (red circles represent existing industrial plants for sugar or ethanol production, black circles represent new industrial plants for ethanol production) in 2030. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

industrial plants, the distribution of available biomass differs considerably. When biomass supply regions are very isolated from industrial processing plants or other supply regions, the available biomass is transported over longer distances instead of building a small industrial plant due to the high investment costs of small industrial plants. For example, in the North of Goiás only one new industrial plant is added to process the additional supply in both the multi-step and one-step optimization approach.

Maps of the expansion of eucalyptus cultivation for ethanol production in the state of Goiás are depicted in Figs. 5 and 6. Eucalyptus cultivation is mainly clustered in the north-eastern part of Goiás. As no existing eucalyptus to ethanol processing plants are currently in place in Goiás, only the multi-step (Fig. 5) and one-step (Fig. 6) optimization approach were carried out. The multi-step optimization approach results in the construction of 42 plants compared to 23 industrial processing plants for the

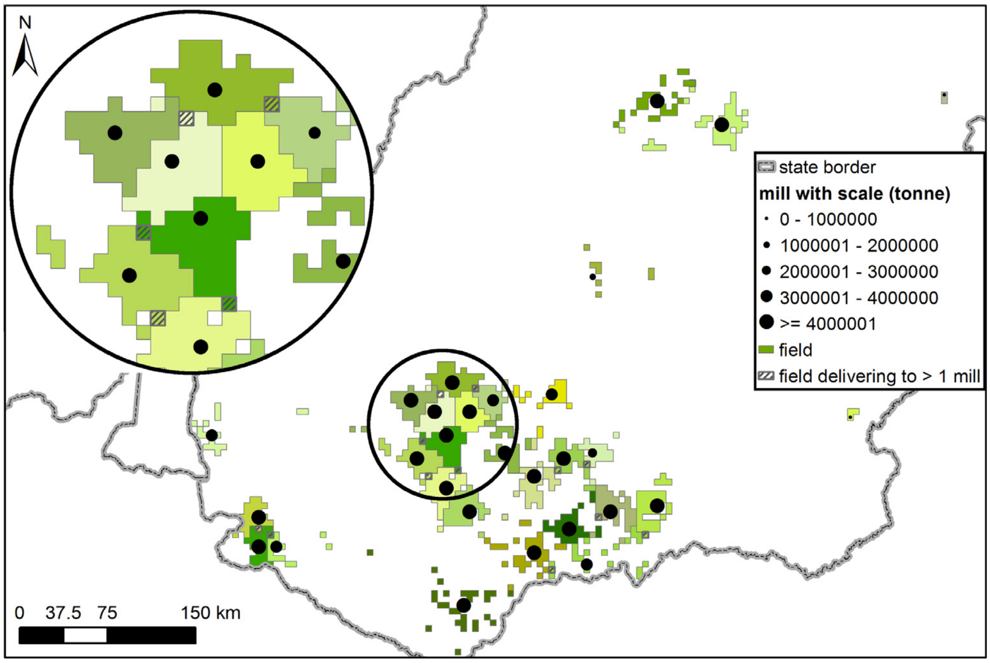

Fig. 4. Map of the greenfield optimization approach (2030) of the sugarcane supply regions in green and industrial plants dedicated to ethanol production in 2030. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

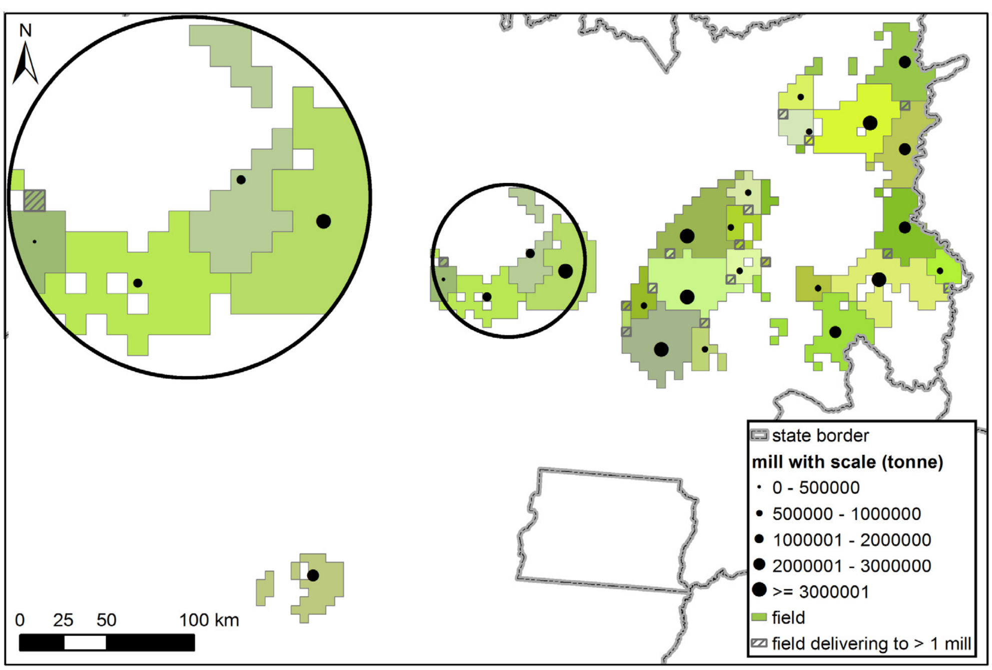

Fig. 5. Map of the one-step expansion approach (2030) of the eucalyptus supply regions in green and industrial plants represented by black circles. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

one-step optimization approach. For the multi-step optimization approach (Fig. 5), the eucalyptus supply increases rapidly over time due to a fast increase in supply regions as well as eucalyptus yield improvement. Due to the clustered eucalyptus supply and economies of scale, the optimization model selects large scale industrial processing plants.

When comparing sugarcane cultivation and processing to eucalyptus cultivation and processing, the optimization prefers large scale industrial processing for both crops. The differences in total amounts of industrial plants of the multi-step and the one-step approach, when comparing eucalyptus to sugarcane, is due to the rapid expansion of eucalyptus supply regions, importance of capital investment in total ethanol production costs of second generation ethanol, and the large allowable industrial scale for industrial processing. To limit transportation costs, the industrial processing plants are placed in biomass supply regions with highest biomass yield. In other words, to obtain the lowest total transportation costs, the region with

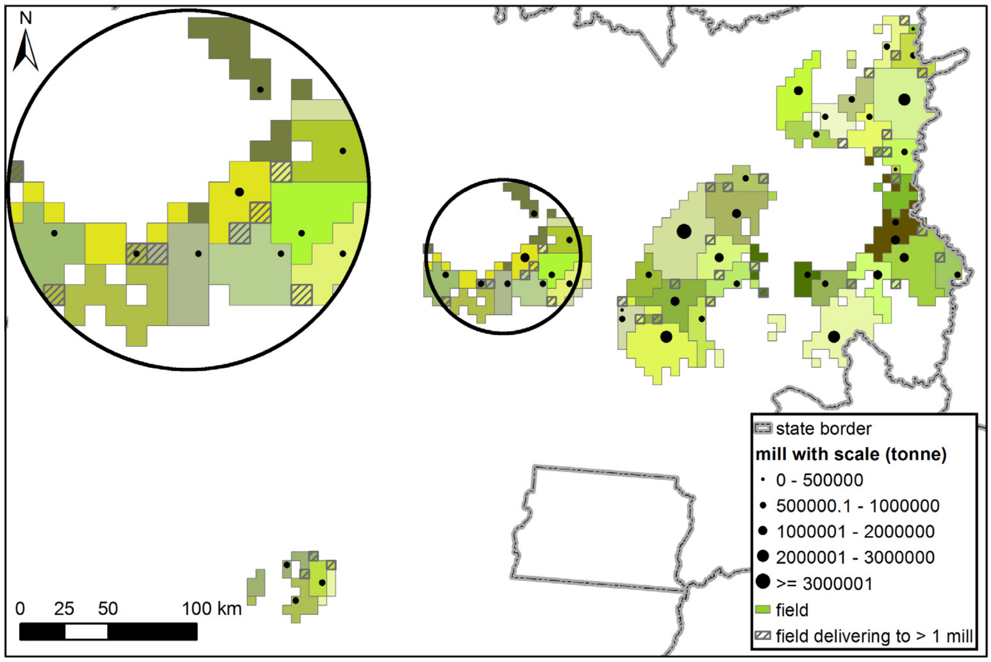

Fig. 6. Map of the multi-step expansion approach (2030) of the eucalyptus supply regions in green and industrial plants represented by black circles. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

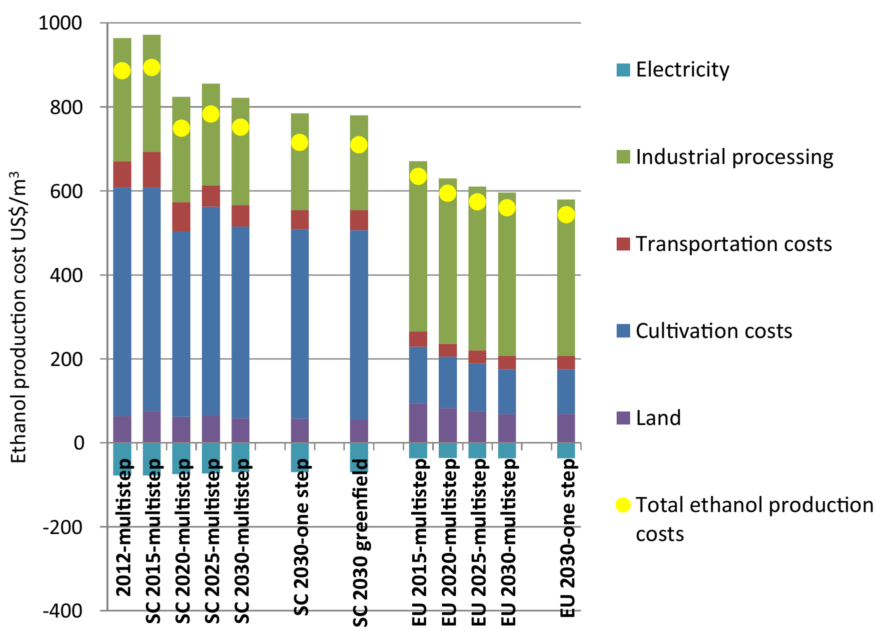

Fig. 7. Average ethanol production cost breakdown utilizing sugarcane (left) and eucalyptus (right) in Goiás for multi-step, (2015, 2020, 2025 and 2030) one-step (2030) and greenfield optimization (2030). Only the cultivation, transport and industrial processing costs of biomass supply regions connected to plants built after 2012 are included.

the highest yield supply is selected for the location of an industrial plant.

5.2. Cost breakdown of ethanol production

Fig. 7 presents the average ethanol production cost breakdown for the expansion of sugarcane and eucalyptus and includes costs for land, cultivation, transport and industrial processing for the multi-step expansion (different time steps up to 2030), one-step expansion (solely 2030), and the greenfield expansion approach (solely 2030). Note that the existing ethanol production facilities are excluded from the cost breakdowns. Only biomass supply regions connected to the proposed new industrial processing plants are considered in Fig. 7, resulting in a small difference in cultivation costs when comparing the multi-step and one-step approach. The total ethanol production costs of 2012 is added as reference value. This value represents the total ethanol production costs determined with the optimization model including all available sugarcane supply regions and existing industrial processing plants in 2012. Under the three different expansion approaches

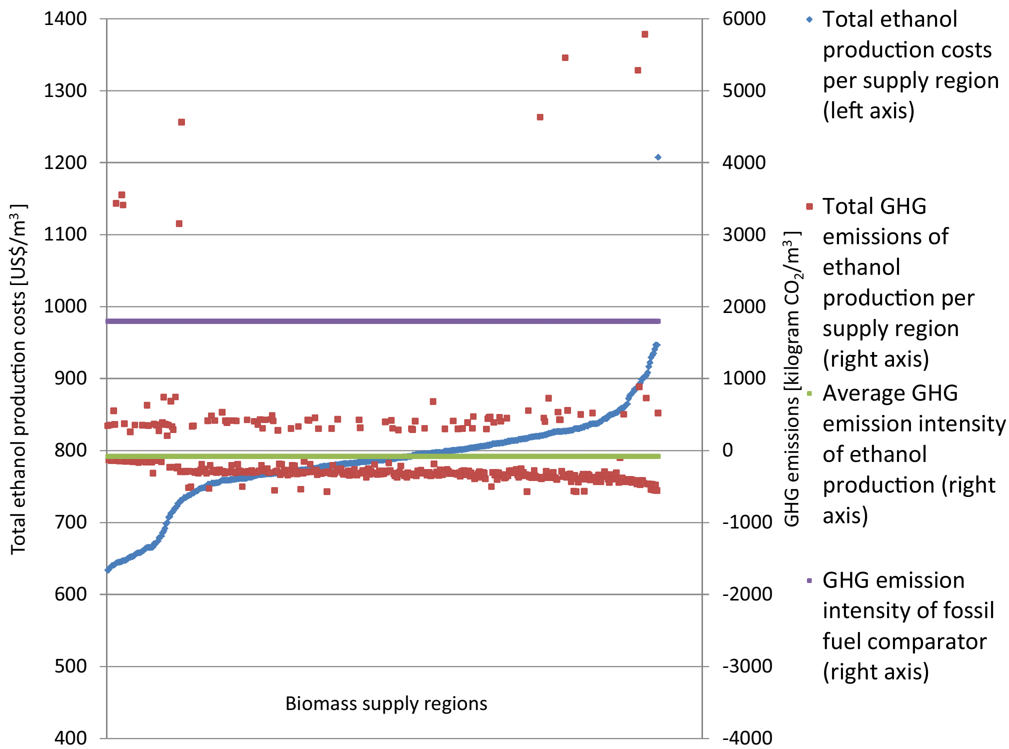

Fig. 8. Costs supply curve of the total ethanol production costs (left *y* axis) of all biomass supply regions in Goiás (each one represented by one dot) delivering sugarcane, including their GHG emission intensity (right *y* axis), average GHG emission intensity (right axis) and the GHG emission intensity of the fossil fuel reference (right *y* axis).

the production costs of sugarcane ethanol decrease from 894 US$/m^3 ethanol in 2015 to 752, 715 and 710 US$/m^3 ethanol in 2030 for the multi-step, one-step and greenfield expansion respectively.

In general, the ethanol production costs for sugarcane processing decline due to yield improvement and the construction of large scale industrial plants. The expansion of sugarcane supply regions between 2015 and 2020 is allocated by PLUC to high biomass yield regions, while after 2020, lower yielding biomass supply regions are taken into cultivation, resulting, on average, in higher cultivation costs in 2025. When comparing the total ethanol production costs in 2030, the main difference among the different expansion approaches is the variation in size of plants, which results in lower capital investment for industrial processing.

For eucalyptus, the ethanol production costs decrease from 635 US$/m^3 in 2012 to 560, and 543 US$/m^3 in 2030 for the multi-step and one-step (greenfield) approach, respectively. In this analysis, there is no difference between one-step expansion approach and the greenfield approach, as there are no ethanol production facilities using eucalyptus currently in Goiás. The capital costs of second generation industrial processing plants are the major element in the total ethanol production costs, even at large scale. Eucalyptus yield improvement is the main driver for the reduction in ethanol production costs in the multi-step approach.

The results depicted in Fig. 7 show a significantly different cost breakdown for sugarcane and eucalyptus-based ethanol production. Despite the fact that second generation processing of ethanol has high industrial processing costs, the total ethanol production costs of eucalyptus processing are lower compared to sugarcane. This is due to the relatively high eucalyptus yield in Goiás, while sugarcane yield is moderate (compared to average Sao Paulo yield levels). Furthermore, due to selection of large scale industrial processing, the economies of scale are exploited for eucalyptus processing by the optimization model. For sugarcane processing also smaller industrial processing facilities are selected, as transport costs are more important for sugarcane.

5.3. Economic ranking and GHG emission intensity of ethanol production

Figs. 8 and 9 show the ethanol production costs (blue[7] points, left axis) and GHG emission intensity (red points, right axis) of ethanol production in 2030 in Goiás using sugarcane (Fig. 8) and eucalyptus (Fig. 9). The ethanol production costs are determined per biomass supply region and ranked according to the total ethanol production costs, from low to high. Also the average GHG emission intensity of all ethanol produced (green line) is shown, as well as the GHG emission intensity of a fossil fuel comparator (purple line).[8] Figs. 8 and 9 only include new biomass supply regions; in other words, only the expansion between 2012 and 2030 is shown. Both Figures present the results of the one-step expansion approach; the two other approaches show a similar pattern, with small differences in the transport and industrial processing costs and GHG emissions (caused by different transport distances).

The cost ranking of ethanol production from sugarcane, as shown in Fig. 8, shows a large variation between the lowest and highest production costs (634–1207 US$/m^3). This is predominantly caused by the variation of sugarcane yields among the biomass supply regions. The sugarcane yield impacts the land costs per tonne harvested biomass of the supply regions but mainly affects the cultivation costs in those regions. For the highest ethanol production costs, also the costs for transport and industrial

[7] For interpretation of colour in Figs. 8 and 9, the reader is referred to the web version of this article.

[8] The GHG emission intensity of the fossil fuel comparator (gasoline) is adjusted for the lower combustion energy of ethanol compared to fossil fuels, and expressed as kg CO_2/m^3 ethanol. This enables the direct comparison with GHG emissions of ethanol production.

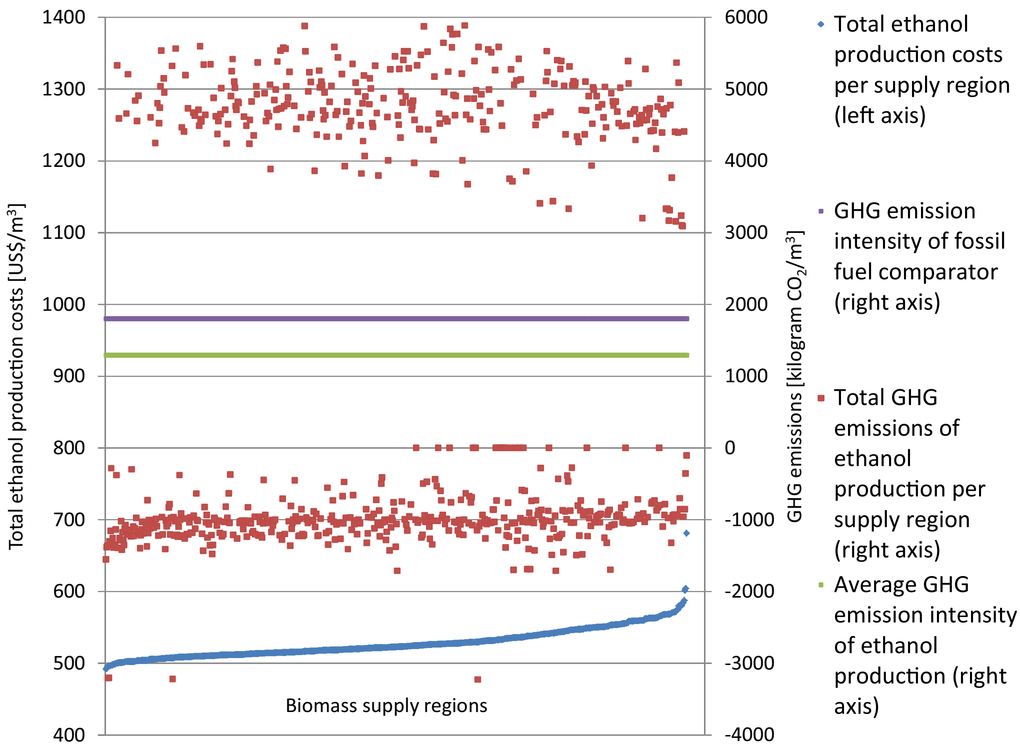

Fig. 9. Costs supply curve of the total ethanol production costs (left *y* axis) of all biomass supply regions in Goiás delivering eucalyptus, including their GHG emission intensity (right *y* axis), average GHG emission intensity (right axis) and the GHG emission intensity of the fossil fuel reference (*y* right axis).

processing are significant. The GHG emission intensity of the ethanol produced are mainly determined by the former land-use carbon stock. The GHG emissions caused by sugarcane cultivation, transport and processing account for between 148 and maximal 490 kg CO_2/m^3. Three main land uses are the basis for the three groups of emission intensities shown in Fig. 8: former cropland (78% of all biomass supply regions in 2030), pasture land (20%) and forested land (2%). Conversion of agricultural land results in negative GHG emissions, ranging between −570 and −100 kg CO_2/m^3 ethanol, as the carbon stock of sugarcane plantation is higher compared to the carbon stock of agricultural land (however, no indirect land-use effects have been taken into account). Note that the supply regions with lower sugarcane yield, commonly on the right side of Fig. 8, have larger negative GHG emissions compared to high biomass yield supply regions. This is due to the net carbon stock gain which is spread over a lower amount of biomass supply. The conversion of pastures results in modest GHG emissions, 205–880 kg CO_2/m^3 ethanol, and the conversion of forested land results in high GHG emissions, ranging between 3150 and 5780 kg CO_2/m^3 ethanol, and thus performs far worse than fossil gasoline. Due to high amounts of cropland being converted to sugarcane plantations, the average GHG emission intensity of ethanol produced in Goiás is −80 kg CO_2/m^3 ethanol in contrast to the fossil fuel competitor of 1800 kg CO_2/m^3 [42].

The cost ranking of ethanol production from eucalyptus, shown in Fig. 9, shows a low variation in ethanol production costs, as the yield variation is low and biomass yield plays a less dominant role in overall ethanol production costs for eucalyptus, as indicated by Fig. 7. The impact of industrial scale on the industrial processing costs is high, but in this study the impact on the industrial processing costs is limited as only large scale industrial plants are selected. For eucalyptus processing, the capital costs of industrial processing are more important than biomass cultivation costs. The range of total ethanol production costs for second generation processing of eucalyptus is between 492 and 681 US$/$m^3$ ethanol, see Fig. 9. The GHG emission intensity for eucalyptus processing shows two main groups of emission intensities: expansion on agricultural land and cropland (59% of all biomass supply regions in 2030) and the expansion on forested land (41%). The eucalyptus cultivation, transport and processing GHG emissions account for 148 to maximal 289 kg CO_2/m^3. The main difference in GHG emissions compared to sugarcane cultivation and processing is due to low transportation costs (high yield and low moisture content) and lower cultivation GHG emissions. High carbon stock of eucalyptus plantations compared to cropland or pasture combined with high ethanol yield result in high avoided GHG emissions of eucalyptus processing in the range of −3220 and 0 kg CO_2/m^3 ethanol. In contrast, the initial carbon stock of forested land causes high GHG emission intensities of ethanol produced from eucalyptus cultivation on former forested land ranging between 3100 and 5890 kg CO_2/m^3 ethanol, see Fig. 9. Therefore, on average, the GHG emission intensity of ethanol production utilizing eucalyptus in Goiás is 1290 kg CO_2/m^3 ethanol, only about 30% lower than the fossil fuel comparator.

Comparing the ethanol production of the two different biomass feedstock in Goiás, the total ethanol production costs of sugarcane is more affected by the yield variation in the biomass supply regions than the ethanol production costs of eucalyptus. Sugarcane cultivation costs are relatively high as Goiás is on average less suitable for sugarcane cultivation. The expansion of eucalyptus cultivation is largely allocated to former forested land, this result in a higher GHG emission intensity compared to sugarcane, which is often allocated to agricultural land. Note that the location of biomass supply regions is determined by PLUC in advance of the utilization of the optimization model.

6. Discussion and conclusion

In this study, the optimization model BioScope is utilized to find the optimal location and scale of industrial plants based on an exogenously given distribution of biomass supply regions as provided by PLUC. The economic objective approach in the linear programming optimization model is the driver for the selection of number and location of plants (reduce transport costs) and sizing (reduce capital costs) of industrial plants. The distribution of biomass supply regions is provided by the land use change model PLUC and is an important element in this optimization study. This novel approach, determining the land distribution in great detail with the land allocation model PLUC, plays a prominent role. The uncertainties of the PLUC model are discussed in [36]. One key aspect when forecasting future land use with PLUC in relation to location-optimization is the *suitability* factor 'travel time to existing mills', as future sugarcane (and eucalyptus) supply regions will most likely deliver to a new industrial processing plants. The locations of future industrial mills are not embedded in PLUC, and therefore, this suitability factor has caused expansion of biomass supply regions in the vicinity of the existing industrial plants. For eucalyptus, PLUC does not include 'travel time to existing mills' as suitability factor. Using the predefined biomass supply regions, potential locations of new industrial processing plants, the transport distance between supply regions and processing plants, and the land use change emissions are also (indirectly) set by PLUC.

The agro-ecological suitability (spatially heterogeneous) and maximum yield value (time variable) jointly determine the biomass yield in the supply regions. The combination of the distribution of biomass supply regions and the varying yields of the supply regions is an important feature of this study and results in the spatial heterogeneous biomass availability. The potential regional variation in plantation management, and its impact on biomass yield, is not considered. However, as most plantations are managed for economic benefits, limited regional variation in plantation management is assumed. Information on spatially explicit sugar cane yield levels in Goiás was not available. Therefore, the maximum attainable biomass yield was based on the relative suitability of biomass supply regions and the total biomass production in Goiás in 2012. Biomass yield also has a strong influence on the biomass cultivation costs, especially for sugarcane cultivation. The variation in biomass supply and biomass cultivation costs is determined by the variation in agro-ecological suitability, as described in Section 3.4.

For the processing of sugarcane, efficient first generation ethanol production in combination with highly-efficient cogeneration is considered, as this is currently the most cost-efficient technology available at commercial scale and already installed in Brazil [8]. For eucalyptus processing, a novel technology is considered, which is still in a research and development stage. To obtain ethanol yields at commercial scale as assumed in this analysis, large upfront investments are required for further development and commercialization of the second generation processing technology. Selecting a novel technology with low industrial processing costs resulted in low ethanol production costs, especially for 2015. Large scale processing is preferred in all expansion approaches, as both industrial processing technology experience economies of scale. The linear relationship between industrial scale and capital costs sets an initial fixed investment, this is mainly important at small scale. The linear relationship between scale and total investment costs for the two scale ranges, as based on [8], have a data fit of 0.99. Therefore, small scale industrial processing is expensive, and transport of biomass to a large industrial plant is most of the times preferred over the construction of a small industrial plant. However, it is uncertain if the ethanol industry is willing to take the financial risk of these large investments. Furthermore, it is highly uncertain if these production cost levels can be met in 2030. Therefore, even though production costs for eucalyptus-based ethanol are projected to be significantly lower in 2030 compared to sugar-case based ethanol, these estimates are inherently more uncertain. Also, as Brazilian ethanol production is currently 100% sugarcane based, it is questionable whether industrial parties will be willing to invest in ethanol production based on eucalyptus. Nevertheless, as the land suitability of Goiás in general is in favour of eucalyptus, the anticipated lower costs combined with the advantages of year-round production (300 vs 170 days of operation) warrant further consideration to develop eucalyptus-based ethanol plants.

Only one preselection criterion is used to determine the potential industrial processing plant locations. In this study, industrial plants can only be planned in biomass supply regions. This preselection had to be considered to avoid long calculation time of the optimization model. As current locations of existing industrial plants are in or in close proximity of biomass supply regions, this assumption is deemed appropriate for Goiás. Other preselection criteria, for example distance between existing mills and large cities (as a proxy for ethanol demand) or distance of the field to a nearby road, were not considered accurate.

The results show that large scale industrial processing is preferred due to clustered biomass supply, low transportation costs and economies of scale for industrial processing. In several cases, the maximum allowable scale as set in the optimization model, restricts the scale of industrial plants. Optimal locations differ among the different expansion approaches used, in most cases industrial plants are preferred in high yielding biomass supply regions to reduce average transportation costs. The differences in total ethanol production costs of sugarcane processing are 894 US$/m^3 ethanol in 2015 and decrease to 752, 715 and 710 US$/m^3 ethanol in 2030 for the multi-step, one-step and greenfield expansion respectively. For eucalyptus, the ethanol production costs decrease from 635 US$/m^3 in 2015 to 560, and 543 US$/m^3 in 2030 for the multi-step and one-step (greenfield) approach respectively. These costs differ only marginally for the different optimization approaches in 2030 due to the utilization of the same biomass supply regions and the small variation in capital investment costs of industrial plants. By optimizing the ethanol production costs for the state of Goiás as region as a whole, the size and location of individual industrial processing plants may be suboptimal locally, but is part of the best overall solution. In reality, different mill owners would obviously aim to minimize ethanol production costs per plant. This situation somewhat resembles the multi-step approach. Compared to the multi-step-approach, the greenfield optimization achieves about 6% lower system-wide overall production costs for sugarcane, and about 3% lower costs for eucalyptus. Thus, under the preconditions used in this study, a system-wide optimization has only a marginal impact on overall production costs. Furthermore, note that boundary effects may occur, as sugarcane and eucalyptus transport to and from industrial plants in neighbouring states is excluded in the current study, but it is difficult to determine how many industrial plants or biomass supply regions are affected due to this effect.

The utilization of PLUC also enables the calculation of total GHG emission intensity of ethanol produced, including land-use change emissions. The calculation of the GHG emission intensity, especially the land-use change emissions, is often neglected in supply chain optimization studies. Due to the conversion of cropland, pasture or formerly forested land the direct carbon emissions or gains due to land-use change dominate the overall GHG emission intensity. However, the land use change emissions or total GHG emission intensity of ethanol was not incorporated in the land use change model or used as optimization objective. Therefore, this analysis shows only the potential GHG emission intensity when the land use distribution and the supply chain design are not optimized for GHG emissions. The GHG emission intensity of ethanol production using the economically optimal supply chain designs is dominated by the direct land use change emissions. It is important to note that only the direct land-use change emissions are taken into account, as this paper does not incorporate the indirect land use change dynamics due to the expansion of ethanol production, meaning that this approach is a strong simplification of the land use change emissions. Due to the predominant expansion of sugarcane cultivation on former cropland, while eucalyptus cultivation expands to a much larger extent on originally forested land, the average GHG emission intensity of sugarcane processing if far lower compared to eucalyptus processing. However, this is only true given the (exogenously determined) distribution of supply regions and does not consider any indirect land use change emissions. Thus, based on the results presented here, a conclusion that sugarcane-based ethanol produced in Goiás would in general have lower GHG emissions than eucalyptus cannot be drawn. In fact, compared to sugarcane, eucalyptus-based ethanol achieves higher direct savings when produced on former agricultural land. However, the results indicate that, due to the importance of land use change emissions, an optimization on minimal overall GHG emissions could yield significant possibilities for GHG emission reductions. Such an analysis would also have to take into account indirect land use change effects, also in relation to other (agricultural) land uses and minimization of supply chain GHG emissions, for example from agricultural inputs. In addition, future ethanol supply chain optimization models could also include a multi-objective optimization procedure to better quantify and optimize the trade-off between GHG emissions and economic performance. In other words; next to the improvement potential addressed in this study, more improvement measures or trade-offs can be quantified in future optimization studies.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apenergy.2016.04.069.

References

[1] IEA. World energy outlook 2013. Paris (France): Corlet, France; 2013.
[2] Lamers P, Hamelinck C, Junginger M, Faaij A. International bioenergy trade—a review of past developments in the liquid biofuel market. Renew Sustain Energy Rev 2011;15:2655–76.
[3] Chum HL, Warner E, Renewable N, Seabra JEA, Macedo IC, Estadual U, et al. Modeling and analysis a comparison of commercial ethanol production systems from Brazilian sugarcane and US corn. BioFPR 2013;19.
[4] Walter A. A sustainability analysis of the Brazilian ethanol; 2008.
[5] Walter A, Dolzan P, Quilodrán O, de Oliveira JG, da Silva C, Piacente F, et al. Sustainability assessment of bio-ethanol production in Brazil considering land use change, GHG emissions and socio-economic aspects. Energy Policy 2011;39:5703–16.
[6] UNICA. Unicadata. Sugarcane harvest reports; 2014.
[7] BNDES. Sugarcane based ethanol for sustainable development. Rio de Janeiro; 2008.
[8] Jonker JGG, van der Hilst F, Junginger HM, Cavalett O, Chagas MF, Faaij APC. Outlook for ethanol production cost in Brazil up to 2030, for different biomass crops and industrial technologies. Appl Energy 2014;14.
[9] Chum H, Faaij A, Moreira J, Berndes G, Dhamija P, Dong H, et al. Bioenergy. United Kingdom: Cambridge; 2011.
[10] Seabra J, Macedo I, Chum H, Faroni C, Sarto C. Life cycle assessment of Brazilian sugarcane products: GHG emissions and energy use. BioFPR 2011:519–32.
[11] González-García S, Moreira MT, Feijoo G, Murphy RJ. Comparative life cycle assessment of ethanol production from fast-growing wood crops (black locust, eucalyptus and poplar). Biomass Bioenergy 2012;39:378–88.
[12] Mele FD, Kostin AM, Guill G, Jim L. Multiobjective model for more sustainable fuel supply chains. A case study of the sugar cane industry in Argentina. Ind Eng Chem Res 2011:4939–58.
[13] Freppaz D, Minciardi R, Robba M, Rovatti M, Sacile R, Taramasso A. Optimizing forest biomass exploitation for energy supply at a regional level. Biomass Bioenergy 2004;26:15–25.
[14] Akgul O, Shah N, Papageorgiou LG. An optimisation framework for a hybrid first/second generation bioethanol supply chain. Comput Chem Eng 2012;42:101–14.
[15] Liu Z, Qiu T, Chen B. A study of the LCA based biofuel supply chain multi-objective optimization model with multi-conversion paths in China. Appl Energy 2014;126:221–34.
[16] Cobuloglu HI, Büyüktahtakın İE. Food vs. biofuel: an optimization approach to the spatio-temporal analysis of land-use competition and environmental impacts. Appl Energy 2015;140:418–34.
[17] Pettersson K, Wetterlund E, Athanassiadis D, Lundmark R, Ehn C, Lundgren J, et al. Integration of next-generation biofuel production in the Swedish forest industry – a geographically explicit approach. Appl Energy 2015;154:317–32.
[18] Samsatli S, Samsatli NJ, Shah N. BVCM: a comprehensive and flexible toolkit for whole system biomass value chain analysis and optimisation – mathematical formulation. Appl Energy 2015;147:131–60.
[19] Mansuy N, Thiffault E, Lemieux S, Manka F, Paré D, Lebel L. Sustainable biomass supply chains from salvage logging of fire-killed stands: a case study for wood pellet production in eastern Canada. Appl Energy 2015;154:62–73.
[20] Marvin WA, Schmidt LD, Daoutidis P. Biorefinery location and technology selection through supply chain optimization. Ind Eng Chem Res 2013:3192–208.
[21] Lin T, Rodriguez LF, Shastri YN, Hansen AC, Ting K. GIS-enabled biomass-ethanol supply chain optimization: model development and *Miscanthus* application. BioFPR 2013;7:314–33.
[22] Giarola S, Zamboni A, Bezzo F. Spatially explicit multi-objective optimisation for design and planning of hybrid first and second generation biorefineries. Comput Chem Eng 2011;35:1782–97.
[23] You F, Graziano DJ, Snyder SW. Optimal design of sustainable cellulosic biofuel supply chains: multiobjective optimization coupled with life cycle assessment and input–output analysis. AIChE J 2012;58.
[24] Lundmark R, Athanassiadis D, Wetterlund E. Supply assessment of forest biomass – a bottom-up approach for Sweden. Biomass Bioenergy 2015;75:213–26.
[25] De Meyer A, Cattrysse D, Rasinmäki J, Van Orshoven J. Methods to optimise the design and management of biomass-for-bioenergy supply chains: a review. Renew Sustain Energy Rev 2014;31:657–70.
[26] Sharma B, Ingalls RG, Jones CL, Khanchi A. Biomass supply chain design and analysis: basis, overview, modeling, challenges, and future. Renew Sustain Energy Rev 2013;24:608–27.
[27] Ferreira Filho JBDS, Horridge M. Ethanol expansion and indirect land use change in Brazil. Land Use Policy 2014;36:595–604.
[28] Eduardo C, Xavier O. CUSTOS DE PRODUÇÃO DE CANA-DE-AÇÚCAR, AÇÚCAR E ETANOL NO BRASIL: ACOMPANHAMENTO DA SAFRA 2011/2012 – CENTRO-SUL 1a Edição Fevereiro de 2012; 2012.
[29] MINISTÉRIO da, AGRICULTURA, MAPA. ANUÁRIO ESTATÍSTICO DA AGROENERGIA. ANUÁRIO ESTATÍSTICO DA AGROENERGIA 2010 2010.
[30] Leal MRLV, Walter AS, Seabra JEA. Sugarcane as an energy source. Biomass Convers Biorefinery 2012;3:17–26.
[31] Johnson FX, Seebaluck V. Bioenergy for sustainable development and international competitiveness. 1st ed.; 2012.
[32] Mello AV, Rezende JB. Anuario Estatistico ABRAF 2013; 2013.
[33] Laércio Couto, Nicholas I, Wright L. Short rotation eucalypt plantations for energy in Brazil; 2011.
[34] Stape JL, Binkley D, Ryan MG, Fonseca S, Loos RA, Takahashi EN, et al. The Brazil eucalyptus potential productivity project: influence of water, nutrients and stand uniformity on wood production. For Ecol Manage 2010;259:1684–94.
[35] IBA. IBA Industria Brasileira de Arvores; 2014.
[36] Verstegen JA, van der Hilst F, Woltjer G, Karssenberg D, de Jong SM, Faaij APC. What can and can't we say about indirect land-use change in Brazil using an integrated economic – land-use change model? GCB Bioenergy 2015. n/a–n/a.
[37] Verstegen JA, Karssenberg D, van der Hilst F, Faaij A. Spatio-temporal uncertainty in spatial decision support systems: a case study of changing land availability for bioenergy crops in Mozambique. Comput Environ Urban Syst 2012;36:30–42.
[38] Verstegen JA, Karssenberg D, Van Der Hilst F. Environmental modelling & software detecting systemic change in a land use system by Bayesian data; 2015.
[39] IIASA/FAO. IIASA/FAO, 2012. Global Agro-ecological Zones (GAEZ v3.0). IIASA, Laxenburg, Austria and FAO, Rome, Italy; 2012.
[40] Geze Toth, Bartosz Kozlowski, Sylvia Prieler DW. Global agro-ecological zones user's guide. Laxenburg, Austria; 2012.
[41] IPCC. IPCC guidelines for national greenhouse gas inventories; 2006.
[42] EC European commission. Report from the commission to the council and the European parliament on sustainability requirements for the use of solid and gaseous biomass sources in electricity, heating and cooling; 2010.
[43] Karssenberg D, Schmitz O, Salamon P, de Jong K, Bierkens MFP. A software framework for construction of process-based stochastic spatio-temporal models and data assimilation. Environ Model Softw 2010;25:489–502.
[44] de Carvalho Macedo Isaias, Leal MRLV, da Silva Jear. Assessment of greenhouse gas emissions in the production and use of fuel ethanol in Brazil; 2004.

[45] Bracelpa. Estatisticas BRACELPA, Relatório Florestal RA02; 2009.
[46] FNP Informa economics. Agrianual 2012. 2012th ed. Sao Paulo; 2012.
[47] Barth M, Youngslove T, Scora G. Development of a heavy-duty diesel modal emissions and fuel consumption model; 2005.
[48] CTBE. CanaSoft (version 0.15). Technological Assessment Program – Brazilian Bioethanol Science and Technology Laboratory (CTBE), Centro National Research Center for Energy and Materials (CNPEM); 2012. <www.bioetanol.org.br>.
[49] Hamelinck CN, Van Hooijdonk G, Faaij AP. Ethanol from lignocellulosic biomass: techno-economic performance in short-, middle- and long-term. Biomass Bioenergy 2005;28:384–410.
[50] Macedo IC, Seabra JEA, Silva JEAR. Green house gases emissions in the production and use of ethanol from sugarcane in Brazil: the 2005/2006 averages and a prediction for 2020. Biomass Bioenergy 2008;32:582–95.
[51] Dias MOS, Cunha MP, Jesus CDF, Rocha GJM, Pradella JGC, Rossell CEV, et al. Second generation ethanol in Brazil: can it compete with electricity production? Bioresour Technol 2011;102:8964–71.
[52] Seabra JEA, Tao L, Chum HL, Macedo IC. A techno-economic evaluation of the effects of centralized cellulosic ethanol and co-products refinery options with sugarcane mill clustering. Biomass Bioenergy 2010;34:1065–78.
[53] MME M de M e E. PLANO DECENAL DE EXPANSÃO DE ENERGIA 2021. Brasilia; 2013.
[54] Hoefnagels R, Smeets E, Faaij A. Greenhouse gas footprints of different biofuel production systems. Renew Sustain Energy Rev 2010;14:1661–94.
[55] Woltjer G, Kavallari A, Van Meijl H, Powell J, Rutten M, Shutes L. The MAGNET model. Wageningen; 2014.